RECENT PROGRESS ON NEURAL NETWORK BASED METHODOLOGY FOR GENERATING ARTIFICIAL EARTHQUAKE ACCELEROGRAMS

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SUMMARY

A new methodology for generating artificial earthquake accelerograms was developed in 1997, which uses the learning capabilities of neural networks to obtain the knowledge of the inverse mapping from the response spectra to earthquake accelerograms. Recently, the methodology has been further extended and enhanced. Due to the stochastic nature of the earthquake accelerograms, it was deemed more appropriate to use stochastic neural networks. A new stochastic neural network has been developed capable of generating multiple earthquake accelerograms for a given response spectrum. The new stochastic features of the neural network is combined with a new strategy for data compression with replicator neural networks. The proposed methodology is more efficient in compressing earthquake accelerograms and extracting their characteristics and it produces a stochastic ensemble of earthquake accelerograms from the design response spectrum. An example is presented to demonstrate the performance of the stochastic neural network and its potential in future research.

INTRODUCTION

"Response spectrum" is often used by structural engineers in designing structures to withstand earthquakes and in evaluating the seismic response of structures. It is defined as the maximum response of an idealized damped single degree of freedom (SDOF) structures subjected to a specified earthquake accelerogram as the ground motion ($\ddot{x}_g(t)$). It is normally plotted as a function of the frequency and damping of the SDOF structure ($S_v(\omega,\zeta)$)[Newmark and Hall, 1982], described as follows:

$$S_v(\omega,\zeta) = \omega \max_t |x(t)| \qquad (1)$$

$$\ddot{x}(t) + 2\xi\omega\,\dot{x}(t) + \omega^2 x(t) = -\ddot{x}_g(t) \qquad (2)$$

Actual earthquake accelerogram records are used when they are available for a given site and earthquake source. Otherwise, artificially generated accelerograms are used. The nonlinear analysis, which would require real or artificial accelerograms, are more likely to be required in the future design codes, thereby increasing the need for artificial earthquake accelerograms.

A design response spectrum, defined as the envelop of possible accelerogram at given site, is used in structural design very oftenly. The artificially generated earthquake accelerograms must be compatible with the design response spectrum, i.e. their response spectrum of the generated accelerogram must closely approximate the design response spectrum. Many researchers have addressed the problem of generating artificial earthquake accelerograms such as Housner and Jennings [1964]; Shinozuka and Sato [1967]; Tsai [1972]; Levy and Wilkinson [1976]; Wong and Trifunac [1979]; Kimura and Izumi [1989]; Haddon [1996]. Recently, the authors have developed an innovative methodology for generating artificial earthquake accelerograms using neural networks [Lin and Ghaboussi, 1997; Ghaboussi and Lin, 1998]. The proposed methodology was successful in learning from the actual recorded earthquake accelerograms and generating realistic artificial accelerograms. This method also allowed

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the development of systematic processing and utilization of the massive volume of the accelerogram records in structural design and analysis. However, only one accelerogram was generated from each design response spectrum since deterministic neural networks were used. Theoriatically, an ensemble of accelerograms should be generated for a given response spectrum because of the random and stochastic nature of the earthquakes. The paper presented here is the extended development and the most updated progress of this method. In this study we present a new stochastic neural network (SNN) and an extension of the original method to generate multiple earthquake accelerograms from one design or response spectrum.

If we consider calculating the spectra from accelerograms as a *forward* problem, then determination of accelerograms from response spectra is an *inverse* problem. The relationship between accelerograms and Fourier spectra are fully reversible and no information is lost form an accelerogram when calculating Fourier spectrum. Consequently, accelerograms can be determined uniquely from Fourier spectra. However, the same is not true for response spectrum. Significant amount of information is lost when the response spectrum is calculated from an accelerogram, and the inverse problem of determining accelerograms from response spectra does not have unique solution [Ghaboussi and Lin, 1998]. This characteristic is present in many inverse problems, the mathematical formulation of many physical problems make their forward relationship unique and their inverse relationship non-unique. The imprecision tolerant learning capabilities of neural networks offer opportunities for solving such non–unique inverse problems. Biologically inspired approach to inverse problems has been discussed in detail in recent paper [Ghaboussi, 1999]. It is possible to develop many accelerograms whose response spectra are close to a given design response spectrum by using stochastic neural networks.

The original method for generating artificial accelerogram used a two stage neural network. First a replicator neural network (RNN) is trained to compress the Fourier spectra of a set of recorded accelerograms. The upper part of the trained replicator neural network relates the compressed Fourier spectrum to the Fourier spectrum. It forms the upper part of the main neural network which relates the response spectrum to the Fourier spectrum [Ghaboussi and Lin, 1998]. In this paper, a new strategy is used to increase the efficiency of the data compression and to reduce the training time for the replicator neural network. Then, a new stochastic neuron model is proposed and implemented in a multi-layer feed-forward (MLFF) neural network to learn to relate the discretized response spectra to the compressed Fourier spectra. The improved method is able to generate many accelerograms from one design response spectrum by combining the replicator neural network and the new stochastic neural network. This new revised method is demonstrated by using a set of one hundred actual recorded accelerograms to train the neural networks and to evaluate its performance by generating accelerograms from novel design response spectra.

NEURAL NETWORKS

Neural networks are one of the biologically inspired soft computing method with massively parallel structure. The unique structures of the neural networks provide the learning capabilities which set them apart from other mathematically formulated methods, and allow the development of the neural network based methods for certain mathematically intractable problems. Neural networks are formed of interconnected artificial neurons. Signals propagate along the connections and the strength of the transmitted signals depend on the numerical weights which are assigned to the connections. Each neuron receives signals along the incoming connection, calculates weighted sum of the incoming signals and an activation function, and then sends signals along its outgoing connections. The operations of each neuron is described as the following Eqs (3), (4) and the knowledge learned by a neural network is stored in its connection weights.

$$U_i = \sum_{j=1}^{m} W_{ij} V_j + I_i \tag{1}$$

$$V_i = f(U_i) = \frac{1}{1 + \exp(-U_i)} \tag{2}$$

m	: the number of neurons in the previous layer of the network,
V_i	: the output signal of neuron i,
U_i	: the net input signal to neuron i,
W_{ij}	: the synaptic interconnection strength, i.e. the connection weight between neuron j and neuron i,
I_i	: the bias input associated with neuron i itself,

For certain difficult engineering problem, it is necessary to design a task-specific neural network rather than just apply a simple neural network to solve the problem even the abilities of the neural network is well known. The complexity of the problem and the very large size of the neural networks used in this study required special attention to the architecture and training of the neural networks. In the presented problem, we applied a combination of the Quick-Prop algorithm [Fahlman, 1988] and local adaptive learning rate algorithm [Cichocki and Unbehauen 1993] to the MLFF neural networks to speed up the rate of learning rate of the networks in this research though the regular back-propagation neural network can also solve this problem within nearly infinite time. Besides, to avoid the neural networks from over-trained for certain patterns, we have also adjusted the algorithm to monitor and equalize the influence on the connection weights of each pattern in the training case during each epoch. In this way we can lower the average root-mean-square output error of the networks as well as keep the generalization ability of neural networks. To determine the number of processing units in the hidden layers, which in turn is related to the complexity of the underlying knowledge base in the training data, a form of adaptive architecture generation developed by Ghaboussi and co-workers [Joghataie, Ghaboussi and Wu 1995] is also used.

We also used a new stochastic neural network to provide the desired random variability of the output in this study. The new stochastic neuron model is proposed by authors after considering some of the recently developed stochastic neural networks and being inspired by stochastic neurons used in Boltzmann machine [Ackley et. al. 1985] and Gaussian machine [Akiyama et. al. 1989]. The detail of this new stochastic neuron and neural network will be described in later section.

A notation which was introduced by Ghaboussi and co-workers [Ghaboussi and Sidarta, 1997; Ghaboussi, et al., 1998] is used to symbolically present the neural networks in a compact form and to facilitate their discussion in this paper. The general form of the notation is,

$$F = \mathbb{NN}\ (\{\text{input parameters}\} : \{\text{NN architecture}\}) \tag{3}$$

where, the symbol $\mathbb{NN}$ denotes the output of a MLFF neural network, and the notation indicates that the vector **F** is the output of the neural network. The first argument describes the input to the neural network, while the second argument field describes the neural network architecture, i.e. the number of processing units in the input layer, the hidden layers, and the output layer, respectively, and its training history.

NEW PROGRESS ON THE PROPOSED METHOD

The objective of this study is to improve the previous developed neural network based methodology to be capable of generating many reasonable artificial accelerograms from one design or response spectrum. The mean of the response spectra of the synthesized accelerograms should match the input design or response spectrum reasonably well. Also, the envelop of response spectra of the synthesized accelerograms should cover every frequency of the input design or response spectrum. Moreover, the accelerograms produced from a given design or response spectrum should have characteristics similar to the group of accelerograms used in the training of the neural networks. The previously developed accelerogram generator neural network (AGNN) takes the discretized ordinates of the pseudo velocity response spectra as input, and produces the Fourier spectra of the generated earthquake accelerograms as output [Ghaboussi and Lin 1998]. By applying a new data compression strategy to the replicator neural network and using the stochastic neural networks, we have developed the multiple accelerogram generator neural network (MAGNN).

In order to obtain groups of artificial earthquake ground motions for different sites, we developed a number of MAGNNs, each trained with a group of real accelerograms sharing certain properties, such as duration, distance from source, magnitude, source characteristics, and site characteristics. In this way the MAGNNs are able to generate accelerograms with the same characteristics.

New Data Compression Strategy for Replicator Neural Network

The architecture of replicator neural networks consist of five layers with identical input and output layers and a much smaller number of neurons in the middle hidden layer. These neural networks are trained to replicate in their output layer the vector given at their input layer. The study by Hecht-Nielsen [1996] indicates that the replicator neural networks perform a mapping from the n-dimensional input vector space to a unit cube in the k-dimensional vector space of middle hidden layer, where k is much smaller than n, and shows that the middle hidden layer of the replicator neural networks produce optimal source codes. We have used the replicator neural networks to accomplish the data compression of the Fourier spectra of the earthquake accelerograms. However, we had used two replicator neural networks to train the real and imaginary part of the Fourier spectra separately [Lin and Ghaboussi, 1997]. In this study we use only one replicator neural network to train both the real and imaginary parts of the Fourier spectra together and we pre-classify the earthquake records by duration. This improvement has considerably speeded up the convergence rate of the replicator neural network. Previously, the training of these very large neural networks (more than two thousand processing units in each of the two neural networks) was time consuming, taking about one week on a HP175/75 workstation for thirty earthquake records [Ghaboussi and Lin 1998]. Now, the computational time is significantly reduced to several hours on a Pentium-II 350 MHz CPU for training a hundred earthquake accelerograms [Lin, 1999].

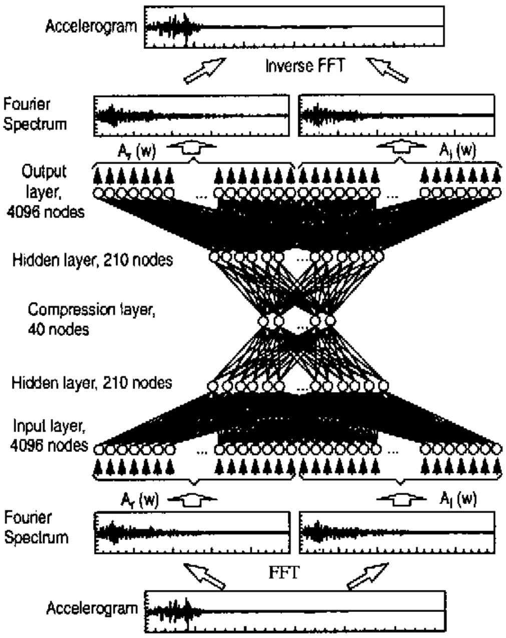

Figure 1. Replicator neural network used for data compression of the Fourier spectra.

Three replicator neural networks were trained for three different earthquakes durations. Figure 1 shows one of the replicator neural networks developed in this study. These replicator neural networks have similar architectures with the same number of neurons in the middle hidden layer. The number of neurons in input/output and the outer hidden layers are different for the long, medium, short duration earthquakes. The output of the replicator neural networks represent the vectors of the real and imaginary parts of the Fourier spectra (denoted by $\mathbf{A_r}$ and $\mathbf{A_i}$) of the replicated accelerograms. The replicator neural network for the long duration earthquakes, shown in Figure 1, is given by the first of the following equations, followed by the replicator neural networks for medium and short duration earthquakes.

$$(A_r + A_i)_{LD} = NN_{LD}\ (\ A_r + A_i)_{LD} :\ 4096,\ 210,\ 40,\ 210,\ 4096\ ) \quad (4)$$
$$(A_r + A_i)_{MD} = NN_{MD}\ (\ A_r + A_i)_{MD} :\ 2048,\ 180,\ 40,\ 180,\ 2048\ ) \quad (5)$$
$$(A_r + A_i)_{SD} = NN_{SD}\ (\ A_r + A_i)_{SD} :\ 1024,\ 100,\ 40,\ 100,\ 1024\ ) \quad (6)$$

In previous studies it was shown that the trained replicator neural networks are capable of reproducing earthquake accelerograms quite well [Lin and Ghaboussi 1997; Ghaboussi and Lin 1998]. Each half of these replicator neural networks can then be considered an independent neural network performing a special function. The lower part of the replicator neural networks (input layer to the middle hidden layer) performs encoding or data compression, while the upper part (middle hidden layer to the output layer) performs decoding or data decompression. The activations of the middle hidden layer, which are the compressed Fourier spectra, are denoted by $\mathbf{A_{(r+i)c}}$. Then the replicator neural network of the Eq (6), (7), and (8) can be written as follows.

$$A_{(r+i)c-LD} = NN_{LD-l}((A_r + A_i)_{LD} : 4096,\ 210,\ 40) \quad (7)$$
$$(A_r + A_i)_{LD} = NN_{LD-u}(A_{(r+i)c-LD} : 40,\ 210,\ 4096) \quad (8)$$
$$A_{(r+i)c-MD} = NN_{MD-l}((A_r + A_i)_{MD} : 2048,\ 180,\ 40) \quad (9)$$
$$(A_r + A_i)_{MD} = NN_{MD-u}(A_{(r+i)c-MD} : 40,\ 180,\ 2048) \quad (10)$$
$$A_{(r+i)c-SD} = NN_{SD-l}((A_r + A_i)_{SD} : 1024,\ 100,\ 40) \quad (11)$$
$$(A_r + A_i)_{SD} = NN_{SD-u}(A_{(r+i)c-SD} : 40,\ 100,\ 1024) \quad (12)$$

It is the upper parts of the trained replicator neural networks, NN_{LD-u}, NN_{MD-u}, and NN_{SD-u} which are used in the MAGNNs.

Stochastic Neural Network for Random Variability Output

In 1985, Ackley et al. used stochastic neurons in Boltzman machines to help the training of the neural networks escape from the local minimum. Inspired by that, the authors propose a new stochastic neuron model, which enables the neural networks not only be able to escape from the local minima but also be capable of generating different real number outputs with a specified statistical distributions. The new model is formed by applying the truncated normal distribution on the activation function of the neuron (Eq. (2)), which is described in the following equations.

$$f(U_i) = \frac{1}{1 + \exp(-U_i)} + \varepsilon \quad (13)$$

$$V_i = \begin{cases} 0 & \text{if } f(U_i) \leq 0 \\ 1 & \text{if } f(U_i) \geq 1 \\ f(U_i) & \text{otherwise} \end{cases} \quad (14)$$

where $\varepsilon \sim N(0, \tau^2)$ is called the activation randomness parameter. The deviation τ of the Gaussian noise ε is called the temperature parameter in this model. The stochastic neural network, denoted by NN_{ST}, is constructed with stochastic neurons in the output layer and the two hidden layers. Eq (15) describes the stochastic neural network we used in this research.

$$\{ A_{(r+i)c} \} = NN_{ST} (S_v : 50, 45, 45, 40) \quad (15)$$

Since the stochastic neurons will produce stochastically different output values during the training, the neural network will be able to learn the underlying knowledge between the response spectra and the compressed Fourier spectra and save that knowledge in its connection weights. Given one design response spectrum as input, the stochastic neural network will be able to produce many compressed Fourier spectra within reasonable range of error. The stochastic neural network has learned to perform the one-to-many inverse mapping task. The number of nodes in the hidden layers of NN_{ST} were determined during the training of the neural network and the stochastic neural network was also trained on one hundred earthquake accelerograms.

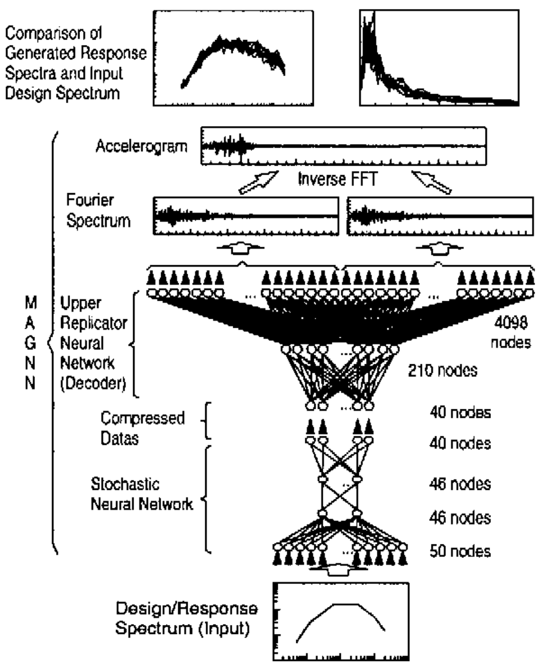

Figure 2. Multiple Accelerograms Generator Neural Network (MAGNN)

Multiple Accelerograms Generator Neural Network

The Multiple Accelerograms Generator Neural Network (MAGNN) is developed to generate the real and imaginary parts of the Fourier spectra of generated accelerograms from the response spectrum. As shown in Figure 2, the MAGNN is composed of two sub neural networks. The lower four layers is the stochastic neural network (NN_{ST}) and the upper part of the MAGNN is the upper part of the replicator neural networks (NN_{LD-u}, NN_{MD-u}, or NN_{SD-u}).

The internal structure of the MAGNN is given by Eq (16).

$$\{A_r + A_i\} NN_{MAGNN}(S_v :) = \{A_r + A_i\} NN_{LD-u}(\{A_{(r+i)c}\} NN_{ST}(S_v :) :) \quad (16)$$

When given a design response spectrum as input, the lower part of the MAGNN (NN_{ST}) generates many compressed Fourier spectra. Each of them then goes through the upper part of the MAGNN (NN_{LD-u}, NN_{MD-u}, or NN_{SD-u}) and becomes Fourier spectrum of generated accelerogram. In this way, the MAGNN is capable of generating many reasonable artificial spectrum compatible earthquake accelerograms from one design response spectrum. As shown in Figure 3, the three MAGNNs we have developed in this study are described in the following equations

$$\{A_r + A_i\} = NN_{MAGNN-LD}(S_v : 50, 45, 45, 40, 210, 4096) \quad (17)$$
$$\{A_r + A_i\} = NN_{MAGNN-MD}(S_v : 50, 45, 45, 40, 180, 2048) \quad (18)$$
$$\{A_r + A_i\} = NN_{MAGNN-SD}(S_v : 50, 35, 35, 40, 100, 1024) \quad (19)$$

for long, medium and short duration earthquakes.

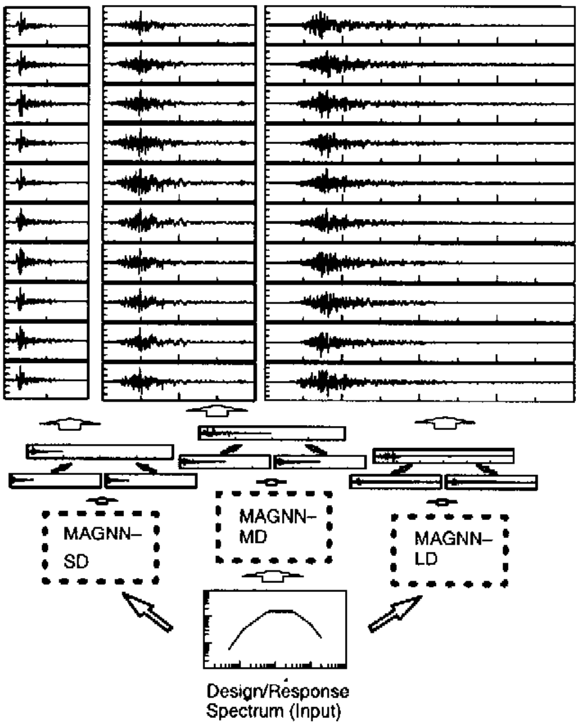

Figure 3. Proposed methodology and the synthesized accelerograms from one design spectrum

AN ILLUSTRATIVE EXAMPLE

The methodology proposed here has been applied to a data sample consisting of a hundred recorded earthquake accelerograms catagorized into three groups by duration for training (training data set) of the neural networks and twenty design spectra for testing of the trained neural networks (test data set). The earthquake accelerograms in the training data set are part of the earthquakes with magnitude greater than 5.0 and recorded from the stations within 50km distance from epicenter (near field) with soft soil condition [S4 type in NEHRP, 1991]. We then scaled the peak ground acceleration (PGA) of all the accelerograms to 0.5g and shifted them to make the PGA of each accelerogeam alined at the same time. All the accelerograms were discretized at 0.02 seconds and the durations of the strong shaking were variable. An arbitrary duration of 20, 40, 80 seconds were chosen for all the accelerograms and sufficient points with zero amplitude were added at the end of each accelerograms to bring the total durations of all the accelerograms to 20, 40, 80 seconds or 1000, 2000, 4000 discrete points. For the purpose of computing the Fast Fourier Transforms of the earthquake accelerograms, they had to be extended to 1024 (2^{10}), 2048 (2^{11}), 4096 (2^{12}), again by adding zero amplitude points to the end of the accelerograms. This resulted in the values of real and imaginary parts of the Fourier spectra at 1024, 2048, 4096 discrete frequencies. After computing the Fast Fourier Transforms of the earthquake accelerograms, they resulted in the values of real and imaginary parts of the Fourier spectra. Only half of each of them were used because of the symmetry about zero frequency. All the points were used as the input and output of the replicator neural networks since complete reversibility is essential.

All the pseudo velocity response spectrua were computed by using the Newmark Beta Method with $\beta = 0.25$ and 2 percent damping. The values of the response spectra were computed at 50 discrete frequencies equally spaced (in log scale) within the range of 0.02 and 50 Hz. All the design spectra were computed by following the guideline developed by Newmark and Hall [1982] with PGA from 0.6g to 1.5g for mean and mean plus one sigma. The values of the design spectra were also computed at 50 discrete frequencies equally spaced (in log scale) within the range of 0.02 and 50 Hz.

Three different MAGNNs were developed, which were composed by three different sets of replicator neural networks and stochastic neural networks, for recorded earthquake accelerograms with long, medium, and short durations. The trained neural networks were tested with the earthquake accelerograms from both the training cases and the novel cases. Comparison of the input and output accelerograms and their response spectra clearly indicates that the trained neural networks have learned the training cases very well. We then used a number of design response spectra as novel cases. The MAGNNs synthesized a number of earthquake accelerograms. The mean of the response spectra of the synthesized accelerograms matches the input design spectrum reasonably well. Similarly, the envelop of response spectra of the synthesized accelerograms covers every frequency of the design spectrum, as shown in Figure 4. Though the response spectrum of each of the synthesized accelerograms does not match the input design spectrum, they are all different and plausible looking accelerograms and the envelope of their response spectra are very close to the input design spectrum.

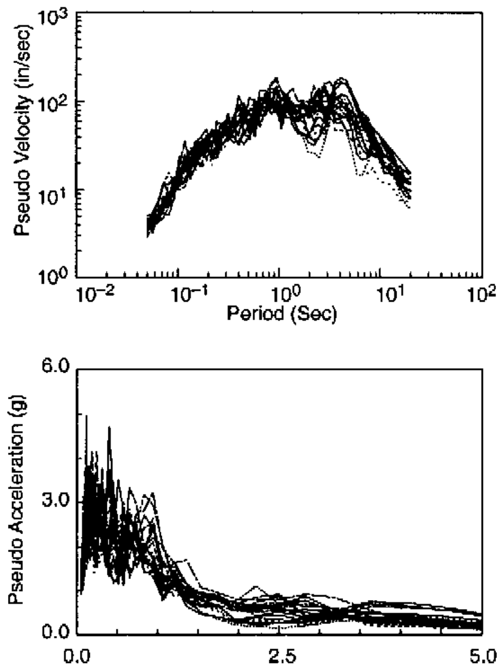

Figure 4. Comparisons of the pseudo velocity response spectra and pseudo acceleration between the generated accelerograms and input design spectrum

CONCLUDING REMARKS

The neural network based methodology for generating spectrum compatible earthquake accelerograms from design response spectra has been improved by incorporating stochastic neurons to produce multiple artificial earthquake accelerograms. The training efficiency of the replicator neural network, used for the data compression of the Fourier spectra, has been considerably enhanced. A new stochastic neuron model is also introduced to form the new stochastic neural network, which is trained to learn to associate the response spectra with the compressed Fourier spectra. The MAGNN is then formed by combining the replicator neural network and the stochastic neural network. The proposed methodology was applied to a sample of one hundred recorded earthquake accelerograms and was found that the MAGNN is able to synthesize ensembles of spectrum compatible and realistic looking accelerograms from an input design spectrum. Moreover, the proposed methodology offers a systematic way of processing and utilizing the increasingly large number of the earthquake accelerograms being recorded with each new earthquake as well as providing a new concept for solving a difficult one–to–many inverse mapping problem.

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REFERENCE

Ackley, D. H., Hinton, G. E. and Sejnowski, T. J., (1985) "A Learning algorithm for boltzmann machines", *Cognitive Science*, Vol.9, pp 147.

Akiyama, Y., Yamashita, A., Kajiura, M., and Aiso, H., (1989) "Combinatorial Optimization with Gaussian machines", *IEEE IJCNN*, Vol. 1, I.533–I.540.

Cichocki, A., and Unbehauen, R., (1993). *Neural networks for optimization and signal processing*, John Wiley & Sons, Chichester.

Fahlman, S. E., (1988) "Faster–learning variations on back–propagation: an empirical study" *Proc. of 1988 Connectionist Models Summer School*, Morgan Kaufmann Los Altos CA, pp.38–51.

Gelenbe, E., (1989) "Random Neural Network with Negative and Positive Signals and Product Form Solution", *Neural Computation*, vol. 1, pp 502–510.

Ghaboussi, J., (1999) "Biologically Inspired Soft Computing Methods in Structural Mechanics and Engineering" *Proceeding, 1st Int'l. Conf. on Advances in Structural Engineering and Mechanics* (ASEM '99), Seoul, Korea

Ghaboussi, J., and Lin, C.-C. J., (1998) "New Method of Generating Spectrum Compatible Accelerograms Using Neural Networks" *Int'l. J. for Earthquake Engineering and Structural Dynamics*, Vol. 27, pp 377–396

Ghaboussi, J., Pecknold, D. A., Zhang, M. and Haj–Ali, R., (1998) "Autoprogressive training of neural network constitutive models" *Int'l. J. for Numerical Methods in Eng.*, Vol. 42, pp 105–126

Haddon, R.A.W., (1996) "Use of empirical green's function, spectral ratios, and kinematic source models for simulating strong ground motion" *Bulletin of the Seismological Society of America*, Vol. 86, No. 3, June, pp597–615.

Hecht–Nielsen, R., (1996) "Data manifolds, natural coordinates, replicator neural networks, and optimal source coding", ICONIP–96

Housner, G, W, and Jennings, P. C., (1964) "Generation of artificial earthquakes" *Journal of the Engineering Mechanics Division*, Proceedings of ASCE, Vol. 90, No. EM1, Feb., pp113–150.

Joghataie, A., Ghaboussi, J., and Wu, X. (1995) "Learning and architecture determination through automatic node generation", ANNIE '95, St. Louis, Missouri.

Kimura, M., and Izumi, M., (1989) "A method of artificial generation of earthquake ground motion" *Earthquake Engineering and Structural Dynamics*, Vol.18, pp867–874.

Levy, S., and Wilkinson, J. P. D., (1976) "Generation of artificial time histories, rich in all frequencies, from given response spectra" *Nuclear Engineering and Design*, v.38, pp241–251.

Lin, C.-C. J., and Ghaboussi, J., (1997) "A New Method of Generating Artificial Earthquake Accelerograms Using Neural Networks" ICCCBE VII, Souel, Korea

Lin, C.-C. J., (1999) "A New Methodology for Generating Artificial Earthquake Accelerogram Using Neural Networks" *PhD thesis*, Dept. of Civil Engineering, Univ. of Illinois at Urbana-Champaign, Urbana, Illinois.

Newmark, N. M., and Hall, W. J., (1982) "Earthquake Spectra and Design" *Monograph* published by Earthquake Engineering Research Institute

NEHRP Recommended Provisions for the Development of Seismic Regulations for New Buildings, 1991 Edition

Shawe–Taylor, J., Jeavons, P., and van Daalen, M. (1991) "Probabilistic Bit Stream Neural Chip: Theory", *Connection Science*, Vol. 3, No. 3, pp 317–328.

Shinozuka, M., and Sato, Y., (1967) "Simulation of nonstationary random process" *Journal of the Engineering Mechanics Division*, Proceedings of ASCE, Vol. 93, No. EM1, Feb., pp11–40.

Specht, D. F., (1990) "Probability Neural Network", *Neural Networks*, vol. 3, pp 109–118.

Tuckwell, H. C., and Rodriguez, R., (1998) "Analytical and Simulation Results for Stochastic Fitzhugh–Nagumo Neurons and Neural Network", *J. Computational Neuroscience*, Vol. 5, pp 91–113.

Tsai, N.-C., (1972) "Spectrum-compatible motions for design purposes" *Journal of the Engineering Mechanics Division*, Proceedings of ASCE, Vol. 98, No. EM2, April, pp345–356.

Wong, H.L., and Trifunac, M.D., (1979) "Generation of artificial strong motion accelerograms" *Earthquake Engineering and Structural Dynamics*, Vol. 7, pp509–527.

Zhao, J., Shawe–Taylor, J. and van Daalen, M., (1996) "Learning in Stochastic Bit Stream Neural Networks", *Neural Networks*, vol. 9, No. 6, pp 991–998.